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Using Bluetooth Low Energy for positioning systems within overcrowded environments: A real in-field evaluation ☆

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ABSTRACT

Bluetooth Low Energy (BLE) is a widely-used technology for short-range proximity and distance estimation. The existence of human bodies is proved to influence BLE signals. In this paper, the effect of overcrowdedness on the performance of BLE-based positioning systems is studied. Real experiments are conducted in places with large and small areas. Both proximity and location beacons are evaluated with different transmission powers. Compared to uncrowded environments, results show random, but often manageable, changes in the received signal strength and position estimation accuracy. The logarithmic path loss model is found unsuitable for small areas and its parameters are noticeably affected by the crowdedness. Location beacons are found more robust against the increase in crowdedness than proximity counterparts. For these location beacons, the overcrowdedness maximally changes the signal strength by 8.6 dBm, the coverage range by 24 m, the proximity estimation accuracy by 18%, and the distance estimation accuracy by 41%.

1. Introduction

Bluetooth is a Wireless Personal Area Network (WPAN) technology for short-range communication. Bluetooth Low Energy (BLE) was presented as a secure low-cost extended version of the classic Bluetooth. In 2016, the latest BLE version, Bluetooth 5, was released with increased range and speed. BLE technology is widely used for estimating positions of BLE-enabled devices. A beacon is a small BLE device that is used to transmit packets in a specific format over short to medium distances. Any BLE-enabled device in the range of the beacon could receive these packets. Using a wireless map or a signal attenuation model, the device could estimate its distance from the beacon. In the literature, two types of beacons are used to accomplish one of two positioning tasks [1]. The first is the proximity beacon, which is used to decide how close a BLE-enabled device is to the beacon. Proximity estimation simply identifies the existence of this device within a certain predefined region. The environment is often divided into three spherical regions whose center is the beacon itself: immediate, near, and far regions [2,3]. The space beyond these regions could not receive any BLE packet and is called the unknown region. The second type of beacons is the location one, which is employed to indicate the actual location of a BLE-enabled device. The logarithmic path loss model is the most widely-used formulation to estimate the location according to the Received Signal Strength Indicator (RSSI) [4]. In practice, both types of beacons are sometimes used

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Nomenclature

ΔE_{un}^{RMS}	Absolute difference between root mean square errors of the overcrowded environment and the uncrowded one.
$\Delta RSSI_{Var}^{avg}$	Average RSSI variation. (i.e., average absolute difference between average RSSI values of the overcrowded environment and the uncrowded one.)
$\Delta RSSI_{Fluc}^{max}$	Maximum RSSI fluctuation. (i.e., maximum absolute deviation of measured RSSI values from the average one.)
$\Delta RSSI_{Var}^{max}$	Maximum RSSI variation. (i.e., maximum absolute difference between average RSSI values of the overcrowded environment and the uncrowded one.)
E^{RMS}	Root mean square error over all estimated distances. (i.e., root mean square error of estimated distances from the actual one.)
η	Path loss exponent. (i.e., rate of BLE signal attenuation with increased distance.)
d	Distance from a BLE-enabled device to the beacon in meters.
d_{toB}^{max}	Maximum distance, at which a proximity estimation error occurs, to the boundary of the correct zone that should be identified.
E^{max}	Maximum error in all estimated distances. (i.e., maximum absolute error of estimated distances from the actual one.)
$\Delta RSSI_{Fluc}^{RMS}$	Root mean square RSSI fluctuation. (i.e., standard deviation of measured RSSI values from the average one.)
AVG	Average value over all experiments.
$N_{Blockage}$	Percentage of experiments in which no BLE signal is received.
R^2	Goodness-of-fit evaluation metric.
RSSI	Received Signal Strength Indicator.
$RSSI_{REF}$	Reference calibrating BLE signal strength for fitting the path loss model.

interchangeably. In this paper, we do not advocate one type of beacons over the other. Rather, we evaluate the performance of both of them.

The accuracy of BLE positioning systems, either proximity or location, depends primarily on the correctness of the RSSI. Ideally, each point within the coverage range of a beacon should receive one specific signal strength that is proportional to its distance from that beacon. In reality, the transmitted signal suffers from different sources of noise and attenuation. As a result, the received signal strength varies from the ideally assumed one. Small variations could probably be tolerated, whereas large ones result in major position estimation errors. Among the many attenuation sources, we herein target the existence of humans within the coverage range of beacons. This existence causes a human body shadowing [5] and moderately obstructs BLE signals [3]. Questions that consequently arise are “what will be the quality of RSSI if the crowdedness is significantly increased?" and “how will the positioning accuracy be affected?". To the best of our knowledge, no previous research work considered this case of overcrowdedness[1]. By overcrowdedness, we mean a people density of at least 2 persons/m^2. Fig. 1 gives examples of this overcrowdedness. In this paper, we conduct experiments in places of large and small areas to assess the impact of overcrowdedness on the performance of BLE-based systems. We aim from these experiments to answer each of the following questions. Finding out these answers constitutes the contributions of our work. Therefore, for the rest of this paper, we refer to these seven questions by the contribution questions.

- **Q1**: How significant does the RSSI vary[2] between uncrowded and very crowded environments?
- **Q2**: How much does the RSSI dynamically fluctuate[3] at the same crowded point from one time to another?
- **Q3**: For both proximity and location beacons, how do variations in RSSI affect the coverage range, which might prevent BLE-enabled devices from receiving services?
- **Q4**: How suitable is it to use the logarithmic path loss model within very crowded environments?
- **Q5**: What are the proper parameters for the logarithmic path loss model within very crowded environments?
- **Q6**: For both proximity and location beacons, how do changes[4] in RSSI affect deciding the region at which a BLE-enabled device exists?
- **Q7**: For both proximity and location beacons, how do changes in RSSI affect the accuracy of estimated distances?

1 The terms “crowded", “very crowded”, and “overcrowded” are used interchangeably in this paper.

2 We use the words “vary” and “variations” to quantify the changes in RSSI values between uncrowded and overcrowded environments.

3 We use the words “fluctuate” and “fluctuations” to quantify the changes in RSSI values between multiple runs of an experiment for the same beacon and at the same distance from that beacon.

4 The term “RSSI changes” encapsulates both “RSSI variations” and “RSSI fluctuations”, as defined in footnotes 2 and 3, respectively.

(a) Crowdedness inside the Prophet's mosque in Almadinah, Saudi Arabia.

(b) Crowdedness in external yards of the Prophet's mosque after prayers.

Fig. 1. Examples of the overcrowdedness that is considered in this paper.
Source: Images are taken from https://www.arabnews.com/node/1356691/saudi-arabia.

The remainder of this paper is organized as follows. Section 2 explains our motivations and the significance of our work. Section 3 surveys the previous related work. Section 4 explains our experimental setup. This includes the configurations of used beacons and the description of the fields in which our experiments are conducted. Section 5 presents our results with a detailed analysis of them to answer our seven contribution questions. Section 6 summarizes our findings and gives limitations of our work. Finally, brief conclusions and future work are provided in Section 7.

2. The need for evaluating BLE performance within overcrowded environments

Overcrowded places are widely spread on Earth. For example, grand places of religious acts, historic locations, amusements places, and shopping areas. BLE is a promising candidate that could provide many services to the visitors of these places. For example, BLE-based applications could be developed to help lost visitors, guide them to landmarks, give them information about the specific location they are in, and pop position-based advertisements to them. To the best of our knowledge, the evaluation of BLE performance within these overcrowded places is not addressed by previous research work. The absence of this evaluation, the widespread of overcrowded places, and the usefulness of using BLE within them all motivate us to carry out this work.

Many factors affect BLE signals in their way from beacons to receiving devices. Most of these factors exist in any field and are summarized as follows. First, reflections from the floor, ceiling, and walls might add to the original signals positively or negatively [2]. Second, the temporal change in environmental conditions, such as the humidity, is shown to affect signals' propagation within the field [1]. Third, interference signals and noise might randomly strengthen or weaken BLE signals [6]. Fourth, the battery of transmitting beacons wears out with time lowering the BLE signal strength from the correct full-battery value [7]. Fifth, obstacles are major factors that obstruct BLE signals causing multipath fading problems. The effect of obstacles of different materials on BLE signals is analyzed in [3]. Sixth, the factor that is unique for overcrowded places is the existence of high people density. The human body is 80% water, which moderately attenuates BLE signals [3]. The effect of the human body on these signals was analyzed and simulated by previous studies [8,9]. These studies found that the human body causes various types of interference with BLE signals, such as reflection, refraction, absorption, and obstruction. Given these findings, the significant increase in people density might severely affect BLE signals. The performance of BLE-based systems within overcrowded places should consequently be assessed. In this paper, we aim to fill this open gap within the BLE research community and fairly evaluate the effect of overcrowdedness on BLE signals. Besides the academic value of this evaluation, we believe that it will be beneficial to manufacturers of BLE devices, responsible authorities of overcrowded places, and BLE-based application developers.

3. Related work

Evaluating the effect of overcrowdedness on BLE performance is barely addressed by previous research work. Numerous studies were however presented for many other research directions. Out of these directions, we consider reviewing two related ones. Section 3.1 surveys the evaluation of BLE performance in lightly and moderately crowded environments. Section 3.2 reviews the deployment and the application of BLE technologies within crowded environments. The numerous research efforts in this latter direction signify the importance of our work of evaluating the impact of overcrowdedness on BLE performance.

Table 1
Summary of surveyed studies that evaluated BLE performance within different environments. (U: Uncrowded; L: Lightly crowded; M: Moderately crowded; Q1…Q7: Our seven contribution questions.).

Ref.	Place	Envir.			Addressed questions						
		U	L	M	Q1	Q2	Q3	Q4	Q5	Q6	Q7
[2]	Indoor, a controlled 48.75 m^2 room and the Expo Museum at Postojna, Slovenia	✓	✓		✓	✓					✓
[4]	Indoor, an office	✓				✓		✓	✓		✓
[5]	Indoor, a 66 m^2 room	✓				✓		✓	✓	✓	✓
[6]	Indoor, a college library; Outdoor, an exterior corridor of a building	✓	✓			✓					✓
[8]	Indoor, a 100 m^2 room	✓	✓	✓	✓	✓		✓	✓		✓
[10]	Indoor, a fair inside a university building	✓	✓		✓	✓				✓	✓
[11]	Indoor, a classroom; Outdoor, on the street		✓				✓				
[12]	Indoor, an ideal anechoic chamber	✓				✓		✓	✓		✓
[13]	Indoor, an obstacle-free college hallway	✓								✓	✓
[14]	Indoor, an unblocked corridor inside a building; Outdoor, an open soccer field	✓	✓			✓	✓	✓			✓
[15]	Indoor, 24 m^2 and 99 m^2 rooms	✓				✓		✓	✓	✓	✓

3.1. Evaluation of BLE performance within lightly and moderately crowded environments

Extensive research was conducted to analyze and quantify the changes in BLE performance between environments of different crowdedness. Throughout our survey, we classify these environments into three categories: uncrowded, lightly crowded, and moderately crowded. The crowd density within these environments is 0, 0–0.5, and 0.5–1 persons/m^2, respectively. Many studies compared RSSI values that are measured in two or the three environments [2,8,10,11]. As the crowdedness increases, random changes in RSSI values and distance estimation errors were observed. Results showed RSSI fluctuations and variations of up to 15 dBm and 10 dBm, respectively. The suitability of using the path loss model was proved for the three environments. Other studies evaluated the effect of changing BLE parameters and techniques on the resultant performance. For example, different orientations [12], transmission powers [6,12,13], advertising intervals [6], numbers of beacons [4,6], vendors [14,15], smartphone platforms [14], and position estimation techniques [5,13,15] were all studied. Table 1 summarizes these studies in a more concise form. For each study, the table gives the environment in which experiments were conducted. Moreover, considering our seven contribution questions in Section 1, the table highlights which questions are addressed by this study. It is important to emphasize that our work differs from these surveyed studies in two main aspects. First, previous research efforts addressed our contribution questions in a light, and rarely moderate, crowdedness while we consider highly crowded environments with a minimum crowd density of 2 persons/m^2. Second, many previous studies were conducted in a controlled synthetic environment while our experiments are carried out in a real very crowded one.

3.2. Deployment of BLE technologies within crowded environments

Many technologies could be used to sense and collect data within crowded environments, such as ZigBee, LoRa, NFC, Sigfox, Wi-Fi, and BLE. Alvear et al. evaluated these technologies with respect to many metrics, including power consumption, cost, availability, size of modules, and ease of deployment [16]. BLE was shown to be the best choice among all these technologies. Consequently, many studies were presented, which deployed BLE technologies within crowded places. Many BLE-based applications were also developed to provide different services to visitors of these places. We herein group previous BLE-based applications into four main categories: data collection, crowd monitoring, route reconstruction, and position-based services. In the first category, BLE technologies are employed to collect data about visitors of crowded locations, such as public events and fairs [17], shopping centers [18], religious worship places [19], and crowded means of transportation [20]. Collected data are then analyzed and processed to understand the crowd behavior and further enhance their experience. In the crowd monitoring category, BLE-enabled devices are tracked throughout the monitored area. BLE-based monitoring is deployed in healthcare units [21], congested roads [22], and public events [11]. Once the crowd density in any place exceeds a certain threshold, a warning mechanism is immediately activated to avoid unpleasant accidents and disasters. The monitoring process also allows authorities to discover suspicious activities and quickly provide the necessary help. In the route reconstruction category, the route of persons/groups within the crowd is sensed and reconstructed. This is useful in discovering bottleneck areas and improving visitors' experience. For example, BLE-based systems were deployed to reconstruct routes of pilgrims during the annual Islamic pilgrimage [19] and visitors to the Little Ding Dong Science Park in Taoyuan, Taiwan [23]. In the position-based services category, BLE technologies are employed to detect the proximity, or location, of customers. Based on this detection, possible services as well as advertisements from nearby stores and facilities are provided to those customers. For example, systems that provide position-based services were deployed in airports [3], universities [14], and motorway tunnels [24]. In a nutshell, Table 2 summarizes articles, which are surveyed in this subsection. The extensive deployment of BLE technologies within very crowded environments necessitates a detailed evaluation of the changes in BLE performance within these environments. Surveyed articles were concerned in deploying BLE technologies for useful applications, rather than carrying out this evaluation. In this paper, we address this challenge by presenting this necessary evaluation of BLE performance within very crowded environments.

Table 2
Summary of surveyed articles that deployed BLE technologies within crowded environments.

Ref.	Reason of deployment	Place of deployment
[3]	Proximity-based services, luggage tracking in airports	Generic, any airport
[11]	Crowd monitoring, tracking during religious, political, or entertainment events. Alarming dangerous overcrowdedness	Generic, any religious, political, or entertainment event
[14]	Location-based services, recording class attendance for university students	Generic, any class with students having BLE-enabled devices
[17]	Data collection, analyzing crowd behavior during entertainment events	A nightclub during the 2016 Amsterdam Dance Event, the Netherlands
[18]	Data collection, analyzing crowd behavior within shopping malls	The Belgian city center shopping mall, Belgium
[19]	Tracing and route reconstruction	Annual Islamic pilgrimage, Makkah, Saudi Arabia
[20]	Data collection, analyzing performance of public transportation systems	Generic, any public transportation system
[21]	Crowd monitoring, tracking within healthcare units	Generic, any healthcare unit
[22]	Crowd monitoring, tracking vehicles within congested roads	Generic, any road with implanted beacons
[23]	Tracing and route reconstruction	Little Ding Dong Science Park in Taoyuan, Taiwan
[24]	Location-based services, emergency evacuation from motorway tunnels	EGNATIA ODOS, the longest motorway tunnel in Greece

4. Experimental setup

In this section, the experimental field, environment, modules, and settings are discussed in detail. Section 4.1 explains employed beacons and their settings, whereas Section 4.2 describes the experimental field and the environment. Using these descriptions, the reader could replicate our work and understand when our conclusions are truly applicable.

4.1. Employed beacons and their configurations

Beacons types and settings are influential factors for any BLE-based analysis and evaluation. In this paper, we follow the findings of Mackey et al. which recommend using Estimote beacons over other vendors [15]. Accordingly, both proximity and location beacons that are employed in our experiments are from Estimote Inc. Proximity beacons are generally cheap, lightweight, and easy-to-use ones, at the expense of having basic features and low specifications. Location beacons are slightly expensive ones, but have improved features and higher specifications. The most crucial feature that noticeably affects the performance of both types of beacons is the transmission power. Therefore, throughout our experiments, we deploy three instances of each type of beacons, which are configured to high, medium, and low transmission powers. Deploying multiple instances of each type, instead of one that is reconfigured repeatedly, is intentionally done to collect our data simultaneously at the same level of crowdedness. Table 3 gives the transmission power that is used with each instance. It also indicates the name that we give to this instance throughout this paper. In detail, for high transmission power, we use the maximum allowable power level for each type of beacons. This is corresponding to 4 dBm for proximity beacons and 10 dBm for location ones. As Estimote only allows the transmission power to be decreased in a step of 4 dBm, the employed medium and low power levels are -4 dBm and -12 dBm, respectively. To differentiate between deployed beacons, we employ the naming conventions of Estimote community. For proximity beacons, the high, medium, and low-power instances are named ice, coconut, and blueberry, respectively. For location counterparts, the corresponding instances are named lemon, beetroot, and candy beacons, respectively.

4.2. Description of experimental field and environment

The main field in which we conducted our experiments is the holy Prophet’s mosque in Almadinah, Saudi Arabia. To assess whether the area of the field affects the BLE performance, we also experimented in a small room whose area is 22.5 m^2. The mosque is one of the largest and most visited religious sites around the earth. During prayers’ time, the crowd density within the mosque is typically higher than 2 persons/m^2, which we target in our evaluation. We carried out our experiments at gate 6 of the mosque. Gate 6 leads to main roads that contain plenty of hotels. Therefore, it often has a higher crowd density than the rest of the mosque and the flow through it is very dynamic. The floorplan of the experimental field is shown in Fig. 2. Beacons are fixed in the six closest posts to the gate at a height of 2 m to increase the probability of having a Line of Sight (LoS) communication. To measure RSSI values from all beacons simultaneously, 6 persons are wandering throughout the field with 6 iPhones X. By doing that, we aim to have almost the same crowdedness in the path of BLE signals of all beacons. The height of each iPhone is fixed at 1.2 m, which is the average height at which people usually carry their smartphones. Starting from each beacon, measurements are done every 3 m, until the signal is totally lost. As measuring at the beacon itself would not give very valuable insights, the very first measurement is exceptionally done at 1 m. The RSSI value at 1 m is indeed useful because it is sometimes used in the literature as the reference power parameter of the path loss model.

Our experiments are conducted during the month of January 2021. To accurately evaluate the effect of overcrowdedness on BLE performance, we repeat our experiments ten times. At each run, we collect data of very crowded as well as uncrowded environments.

Table 3
Used names and transmission powers for deployed proximity and location beacons.

Beacon type	Proximity			Location		
Used name	Ice	Coconut	Blueberry	Lemon	Beetroot	Candy
Transmission power (dBm)	High (4*)	Medium (−4)	Low (−12)	High (10*)	Medium (−4)	Low (−12)

*: Maximum allowable transmission power.

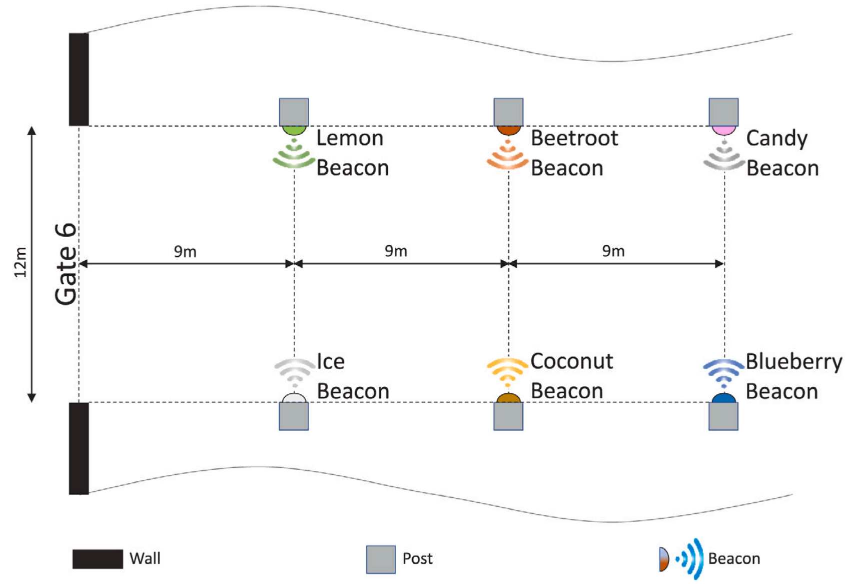


Fig. 2. Experimental field. (i.e., Floorplan of the section of the Prophet's mosque, in which we conducted our experiments.).

For the very crowded environment, the data are collected immediately after the late-night prayer, namely Isha'a prayer, when the crowd density is extremely high. For the uncrowded environment, our experiments are repeated with the same settings at midnight, when the mosque is unattended. As our experiments span different days and time intervals, there were some changes in the environmental conditions. However, these changes are really minor and do not affect the accuracy of our evaluation. During the time of different experiments, the temperature ranges from 11–17°C and the humidity ranges from 39%–47%. The air quality is measured moderate with an Air Quality Index (AQI) that ranges from 52–57 $\mu g/m^3$.

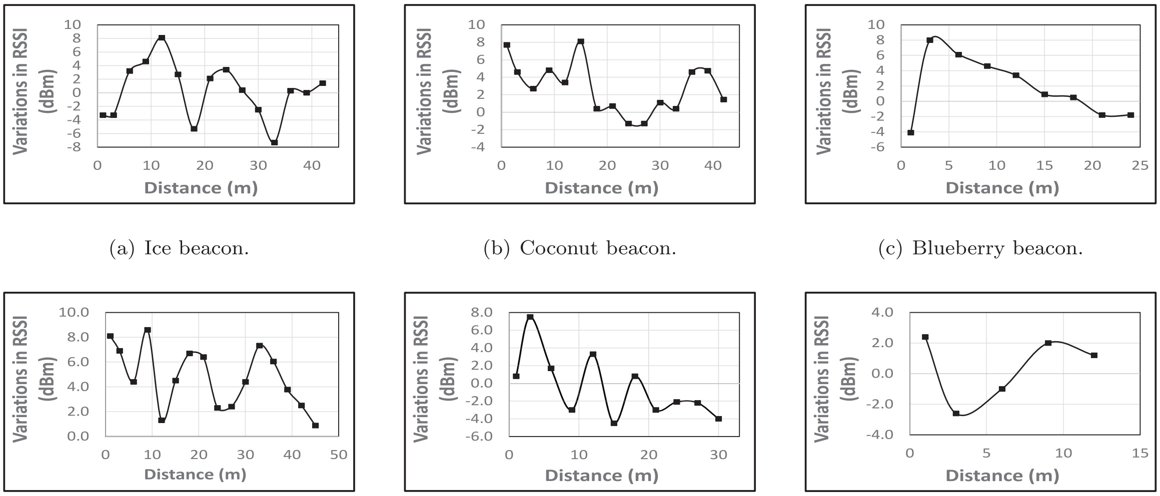
5. Evaluation of BLE performance within overcrowded environments

In this section, we present our experimental results to quantify the effect of overcrowdedness on BLE performance. By analyzing obtained results, we find answers to our contribution questions. To better explain our findings, we have a dedicated subsection for each contribution question to present and discuss its corresponding results.

5.1. Evaluation of RSSI variations between uncrowded and overcrowded environments

We start our discussion by investigating our first contribution question of how significant do RSSI values vary between uncrowded and overcrowded environments. For each proximity and location beacon, we average RSSI values, which are measured in different experiments, at every considered distance from that beacon. Fig. 3 presents the difference between these uncrowded and overcrowded averages. We present results for distances, at which BLE signals are received in both environments. Positive variations indicate that the uncrowded signal is stronger than its overcrowded counterpart, whereas negative variations reflect the contrary. From this figure, we have five conclusions.

- The variations in RSSI values between uncrowded and overcrowded environments are completely random. Except for the lemon beacon, the overcrowded signal might randomly be stronger or weaker than its uncrowded counterpart. We return this randomness to the many reflections that occur by the continuous flow of people. These reflections might superimpose on the original BLE signal positively or negatively. This randomly strengthens or weakens the received signals and causes the RSSI to vary in such a represented manner. Considering this resultant randomness, our findings agree with previous studies in lightly and moderately crowded environments [2,8].



(a) Ice beacon. (b) Coconut beacon. (c) Blueberry beacon.

(d) Lemon beacon. (e) Beetroot beacon. (f) Candy beacon.

Fig. 3. Average RSSI variations between uncrowded and overcrowded environments for considered beacons. (Proximity beacons are at the top and location ones are at the bottom.).

- RSSI variations between uncrowded and overcrowded environments are quite small. These variations extend from a minimum of −7.3 dBm, for the ice beacon, to a maximum of 8.6 dBm, for the lemon beacon. Variations of this scale are typical in any BLE-based positioning system. Accordingly, we safely conclude that the effect of overcrowdedness on RSSI values should not prevent BLE from being used in very crowded environments. Previous accuracy-enhancing techniques could still be used to realize good position estimations in these environments.
- There is no much difference between proximity and location beacons with respect to the resultant randomness in RSSI values. Nonetheless, the range of variations, i.e., the difference between maximum positive and minimum negative variations, slightly favors location beacons. Numerically, for proximity beacons, these ranges are 15.4 dBm, 9.4 dBm, and 12.1 dBm for ice, coconut, and blueberry beacons, respectively. For location beacons, the same three ranges for lemon, beetroot, and candy beacons are 7.7 dBm, 12.0 dBm, and 5.0 dBm, respectively.
- For both proximity and location beacons, RSSI variations are independent of the transmission power. For location beacons, the medium-power beetroot beacon has a greater variation range than high-power lemon and low-power candy beacons. In contrast, for proximity beacons, the medium-power coconut beacon has a lower range than the other two low-power and high-power ones.
- RSSI variations are independent of the distance from the beacon. Random variations of variable magnitude are seen at different distances.

5.2. Evaluation of RSSI fluctuations between different runs

In our second contribution question, we evaluate the effect of overcrowdedness on the amount of fluctuations, which occur in RSSI values between different runs of our experiments. Accordingly, results of the very crowded environment are only included and discussed in this subsection. Table 4 summarizes these results for both proximity and location beacons. In our evaluation, we consider two types of fluctuations, major and minor ones. In major fluctuations, the BLE signal is blocked in some runs while received in others, at the same distance from the beacon. They might alternatively be named signal blockage fluctuations. The impact of major fluctuations is to hang up the system and stop BLE-based services. In our table, the $N_{Blockage}$ columns quantify the percentage of experiments, in which no BLE signal is received. The range and the average of these percentages are both included in the table. In minor fluctuations, no blockage occurs and the BLE signal is received successfully in multiple runs of our experiments. However, the received RSSI value differs from one run to another. Unlike major fluctuations, minor ones would not completely lock up the system. Rather, according to the magnitude of the fluctuations, they might impact the accuracy of the position estimation process. In our evaluation, minor fluctuations are quantified by two statistical metrics, the Root Mean Square (RMS) deviation ($\Delta RSSI^{RMS}_{Fluc}$) and the maximum absolute deviation ($\Delta RSSI^{max}_{Fluc}$). At each distance from the beacon, both metrics are calculated as percentages of the average RSSI value at this distance. Over all distances, the range and the average of the two metrics are found and included in Table 4. From this table, we have four conclusions.

- Except for the lemon beacon, very crowded environments do not much suffer from major fluctuations and total signal blockage. The occurrence of these fluctuations for the lemon beacon is an apparent example of the randomness, which occurs within very crowded environments. For the other five beacons, major fluctuations only happen at the end of the coverage range of coconut and blueberry ones. Otherwise, the BLE signal is always received in all our experiments.

Table 4
Evaluation of RSSI fluctuations in the overcrowded environment for considered proximity and location beacons.

Beacons		$N_{Blockage}$ (%)		$\Delta RSSI_{Fluc}^{RMS}$ (%)		$\Delta RSSI_{Fluc}^{max}$ (%)	
		Range	AVG	Range	AVG	Range	AVG
Proximity beacons	Ice	– –	0.0	1.2–3.5	1.9	1.8–7.5	3.4
	Coconut	0–60	7.3	0.0–6.9	2.2	0.0–12.7	4.2
	Blueberry	0–20	2.0	1.0–2.7	1.8	1.9–6.2	3.2
Location beacons	Lemon	0–80	13.1	0.0–1.8	1.1	0.0–3.9	1.7
	Beetroot	– –	0.0	0.5–2.5	1.4	1.0–7.0	2.8
	Candy	– –	0.0	1.3–2.3	1.8	1.6–5.3	3.2

- Similar to RSSI variations in the previous subsection, the amount of RSSI fluctuations is small for both proximity and location beacons. For proximity beacons, the largest RMS deviation is 6.9% and the largest maximum absolute deviation is 12.7%. This slightly high 12.7% deviation occurs only once for the coconut beacon. Otherwise, the maximum absolute deviation never exceeds 7.5%. For location beacons, the largest RMS deviation is 2.5% and the largest maximum absolute deviation is 7.0%. Based on these small fluctuations, we again conclude that changes in RSSI values due to the overcrowdedness could still be handled by accuracy-enhancing techniques that are currently used in BLE-based positioning systems.
- Location beacons have less fluctuations than their proximity counterparts. For proximity beacons, the average of maximum absolute deviations over all distances is 3.4%, 4.2%, and 3.2% for ice, coconut, and blueberry beacons, respectively. For location beacons, the corresponding averages are 1.7%, 2.8%, and 3.2% for lemon, beetroot, and candy beacons, respectively. In conclusion, once a steady signal is of interest, location beacons appear more stable against RSSI fluctuations and are better employed within very crowded environments than proximity ones.
- Similar to RSSI variations in the previous subsection, the observed fluctuations are independent of the distance and the transmission power. In our experiments, fluctuations of variable magnitudes are seen at different distances and transmission powers.

5.3. Evaluation of variations in coverage range

In our third contribution question, we evaluate how the overcrowdedness affects the BLE signal reception around the beacon. In this subsection, we consider two ranges for comparison and evaluation. The first range is the distance beyond which the BLE signal is not received for at least one run of our ten runs. In other words, this range is the maximum distance at which the BLE signal is always received. After this distance, the signal may disappear and we enter a zone of BLE uncertainty. Analogous to the setting down of the sun, we name this range the afterglow range. The second range is the distance beyond which the BLE signal is never received. Consequently, this range is the maximum distance at which the BLE signal is received at least once in our ten runs. After this distance, the signal completely disappears and we enter a zone of BLE darkness. This latter range is the most widely used one in the literature and is often named the coverage range. For any BLE-enabled device, being covered by a beacon simply means that the device could receive its signal and use it for position estimation. Fig. 4 shows the zones around the beacon and the relation between these zones and the two considered ranges. Fig. 5 compares measured ranges of the uncrowded environment to those of the overcrowded one. Starting by evaluating the effect of overcrowdedness on the coverage range, we have four conclusions.

- Other than the blueberry beacon, the coverage range in the uncrowded environment is always larger than that of the overcrowded one. The existence of too many people apparently obstructs BLE signals and reduces the coverage range within the overcrowded environment. The blueberry beacon is affected by its lower transmission power, and hence, its uncrowded and overcrowded ranges are equal.
- The difference between ranges of the two environments is large for location beacons than for proximity ones. Numerically, for location beacons, the overcrowded coverage ranges are 65.2%, 83.3%, and 66.7% of the uncrowded ones for lemon, beetroot, and candy beacons, respectively. For proximity beacons, these percentages are 82.4%, 92.3%, and 100% for ice, coconut, and blueberry beacons, respectively. As a result, extra care should be taken when deploying location beacons in an overcrowded environment. The deployment should be done considering a major reduction in the coverage range and more rigorous techniques should be employed for enhancing the accuracy.
- The maximum difference between uncrowded and overcrowded coverage ranges occurs for the highest transmission power, i.e., for lemon and ice beacons. For the lemon beacon, this difference reaches 24 m. Many previous articles advocated using high transmission power to enhance the system performance. Consequently, the significant reduction in the coverage range should be carefully considered if a high crowd exists in the deployment area.
- As the transmission power is reduced from the highest to the lowest values, the corresponding decrease in the coverage range is steeper for location beacons than proximity ones. This occurs in both uncrowded and overcrowded environments. For example, for the uncrowded environment, the coverage range decreases from 69 m to 18 m for location beacons, while it decreases only from 51 m to 27 m for their proximity counterparts. Accordingly, dynamic reduction of the transmission power for location beacons should be done wisely to avoid performance degradation and system failure.

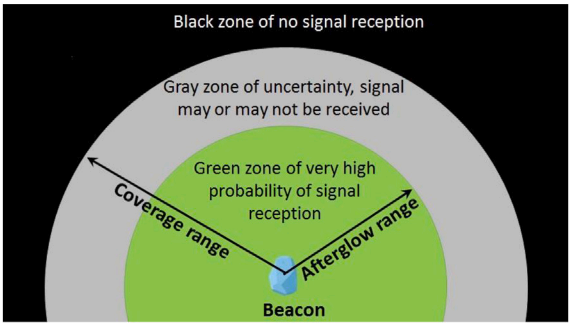
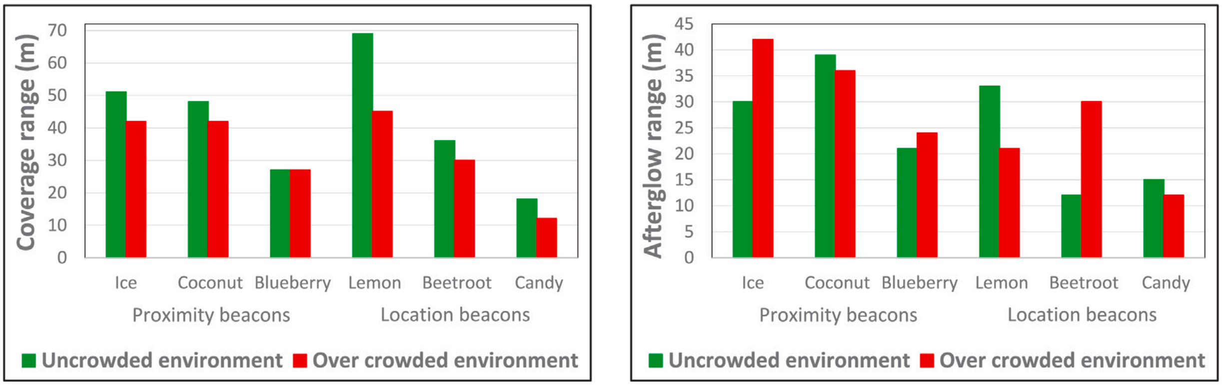


Fig. 4. Zones around the beacon and their relation to the afterglow and coverage ranges.



(a) Coverage range.

(b) Afterglow range.

Fig. 5. Comparison between uncrowded and overcrowded environments with respect to their coverage and afterglow ranges for considered proximity and location beacons.

For the afterglow range, we have three conclusions.

- Consistent with our RSSI variation results in Section 5.1, changes in afterglow ranges occur totally random. This randomness is witnessed in many aspects. First, a beacon with less transmission power might arbitrarily have a larger afterglow range than another one, whose transmission power is higher. Second, the range in the uncrowded environment may randomly be larger, or smaller, than its corresponding overcrowded one. Third, the difference between ranges of the two environments itself changes completely random for different beacons. Numerically, this difference reaches as high as 18 m, for the beetroot beacon. This randomness again returns to the high dynamics that are associated with large gatherings of people. The dynamic roaming and movement of the too much crowd cause random absorption, reflection, shadowing, and obstruction of BLE signals.
- Unlike RSSI variations and fluctuations in the previous two subsections, changes in afterglow and coverage ranges are significant. A “be safe" advice is probably the best one that should be given. The deployment of beacons should be done in a way that ensures receiving their signals by all surrounding devices. For a power-independent deployment, the minimum afterglow range for each type of beacons should be safely assumed as their coverage range. Accordingly, a range of 21 m for proximity beacons highly assures a proper signal reception by surrounding BLE-enabled devices. This is corresponding to the value of the lowest bar for proximity beacons in Sub Fig. 5(b). For location beacons, the safe range reduces to 12 m.
- The difference between the coverage range and its afterglow counterpart, i.e., the gray zone of BLE uncertainty, is bigger for location beacons than for proximity ones. Numerically, for location beacons, this difference reaches up to 36 m, for the lemon beacon. For proximity beacons, the difference reaches up to only 21 m, for the ice beacon. The figure also shows that the difference between coverage and afterglow ranges is larger for high transmission power. This again emphasizes giving extra care while deploying location beacons, especially when using high transmission power.

5.4. Suitability of the logarithmic path loss model and finding its parameters

In this subsection, we target two of our contribution questions, the fourth and the fifth. We verify the suitability of using the logarithmic path loss model within very crowded environments and find its parameters. The path loss model is the most widely used

Table 5
Fitting parameters resulted from the LSR method as well as the R^2 goodness-of-fit metric for considered proximity and location beacons.

Beacons		RSSI (1 m)	Parameters		R^2
			$RSSI_{REF}$	η	
		(dBm)	(dBm)		(%)
Proximity beacons	Ice	−62.1	−59.0	1.46	83.01
	Coconut	−72.9	−68.1	1.17	59.13
	Blueberry	−68.6	−71.0	1.39	88.49
Location beacons	Lemon	−61.8	−56.8	1.94	92.79
	Beetroot	−64.3	−63.3	1.88	95.57
	Candy	−77.5	−74.7	1.60	80.78

one to formulate the attenuation in the BLE signal while increasing the distance from the beacon. Using this model, BLE-enabled devices utilize the received RSSI value to estimate the distance from the beacon. The path loss model is formulated as.

$$RSSI\,(d) = RSSI_{REF} - 10 \cdot \eta \cdot log\,(d) \tag{1}$$

Where $RSSI(d)$ is the BLE signal strength at distance d from the beacon. η is the path loss exponent, which indicates how fast the BLE signal is attenuated with the distance. $RSSI_{REF}$ is a reference calibrating BLE signal strength for fitting the model. In our work, we find two fitting parameters for each beacon, η and $RSSI_{REF}$. According to the measured data of each beacon, we use the Least Square Regression (LSR) method to find the best fitting curve. For each resultant curve, the R^2 goodness-of-fit evaluation metric [25] is calculated to quantify the suitability of using the path loss model within very crowded environments. This metric uses a scale from 0% to 100% to indicate the quality of the model in fitting the measured data. The higher the value of R^2, the better the fitting is. Table 5 gives the parameters resulted from the LSR fitting process as well as the value of R^2 goodness-of-fit metric for each beacon. From the figure and the table, we have four conclusions.

- Except for the coconut beacon, the R^2 metric reflects a good fitting quality with values exceeding 80%. These high R^2 values indicate that the logarithmic path loss model could suitably be used within very crowded environments to estimate the distance based on the value of RSSI.
- The path loss model has better fitting quality for location beacons than for proximity ones. Numerically, for location beacons, R^2 values are 92.79%, 95.57%, and 80.78% for lemon, beetroot, and candy beacons, respectively. The corresponding values for proximity beacons are 83.01%, 59.13%, and 88.49% for ice, coconut, and blueberry beacons, respectively. These results are logical because location beacons are employed for accurate distance estimation, whereas proximity counterparts only indicate the closeness of BLE-enabled devices to beacons.
- Values of $RSSI_{REF}$, which are obtained through the fitting process, are close to measured signal strengths at 1 m. By comparing the two corresponding columns in Table 5, the maximum difference between them is 5 dBm, for the lemon beacon. As a result, the widely-used assumption of employing the RSSI at 1 m as calibrating signal strength in the path loss model is correct for very crowded environments.
- For location beacons, path loss exponents, η, are close to 2. This agrees with the previous validation of the model in moderately crowded environments [8]. For proximity beacons, this is not accurate as the exponent lowers down to 1.17.

5.5. Evaluation of proximity estimation accuracy

Proximity estimation is the process of detecting BLE-enabled devices that exist close to beacons. It is further extended in the literature to represent the process of identifying a pre-defined zone based on the received RSSI value. In this subsection, we follow the widely-used division of the environment into three adjacent zones: immediate, near, and far. The advantages of using this division in our evaluation are two-fold. First, having three zones enables us to evaluate two types of errors. The first is a minor one, in which the correct zone is not identified, but an adjacent one. For example, a near zone might be incorrectly identified instead of an immediate one and vice versa. The second type of errors, which could not be evaluated using only two zones, is a major one. In this type, the system indicates a non-adjacent zone to the correct one. For example, the system might erroneously indicate a far zone instead of an immediate one and vice versa. The second advantage of using the adjacent three-zone division is to allow us to decide a suitable spacing between zones in real-life applications. Having zero-spaced adjacent zones enables us to conduct experiments everywhere within the field. Through these experiments, we discover areas, in which estimation errors occur. These areas should consequently be avoided and zones should be spaced in accordance. In order to establish the three zones in our experiments, we divide the coverage range of each beacon into three equal segments. For example, the coverage range of the blueberry beacon is 27 m. Accordingly, the immediate zone has a maximum radius of 9 m from the beacon. The near zone spreads from 9 m to 18 m from the beacon and the far zone starts from 18 m till the end of the coverage range. Many experiments are then done at different distances from each beacon. These experiments are uniformly distributed within the coverage range to thoroughly evaluate the proximity estimation accuracy in all areas of the field. In proportion to the coverage range, 100 to 150 experiments are done for each beacon, except candy. For this latter beacon, the coverage range is short, i.e., 12 m, and only 50 experiments are done. For each experiment,

Table 6
Evaluation of the proximity estimation accuracy for considered proximity and location beacons.

Beacon		Environment	Estimation accuracy					Most repeated error
			Correct	One-zone error		Two-zone error		
			%	%	d_{toB}^{max} m	%	d_{toB}^{max} m	
Proximity beacons	Ice	Uncrowded	68.94	31.06	10	0.00	N/A	Near → Immediate
		Very crowded	72.67	26.67	10	0.67	19	Near → Immediate
	Coconut	Uncrowded	68.46	31.54	10	0.00	N/A	Near → Immediate
		Very crowded	57.55	40.29	13	2.16	16	Near → Immediate
	Blueberry	Uncrowded	65.56	34.44	6	0.00	N/A	Near → Immediate
		Very crowded	71.43	28.57	6	0.00	N/A	Far → Near
Location beacons	Lemon	Uncrowded	75.52	24.48	6	0.00	N/A	Far → Near
		Very crowded	87.77	12.23	6	0.00	N/A	Far → Near
	Beetroot	Uncrowded	86.25	13.75	2	0.00	N/A	Near → Immediate
		Very crowded	81.82	18.18	4	0.00	N/A	Near → Far
	Candy	Uncrowded	100.00	0.00	N/A	0.00	N/A	N/A
		Very crowded	82.00	18.00	2	0.00	N/A	Near → Immediate

the zone is estimated and compared to the correct one that should be obtained. Over all these experiments, we calculate the number of times in which the zone is estimated correctly, or erroneously. As mentioned at the beginning of this paragraph, the error might be a minor one-zone or a major two-zone one. The estimation accuracy is then calculated as the percentage of the number of correct estimations to the total number of experiments. For one-zone and two-zone errors, the severity of each of them is quantified by the maximum distance, d_{toB}^{max}, at which an erroneous estimation occurs with respect to the boundary of the correct zone. In other words, d_{toB}^{max} recognizes how far do errors occur from the correct zone that should be identified. It consequently represents the spacing that should be kept between zones to avoid incorrect estimations. Table 6 shows our results for both proximity and location beacons. From this table, we have four conclusions.

- The estimation accuracy in the very crowded environment might randomly be higher or lower than that in the uncrowded one. The percentage correct estimation for ice, blueberry, and lemon beacons is higher in the very crowded environment than the uncrowded one. In contrast, it is lower for coconut, beetroot, and candy beacons. Similar to our discussion in Sections 5.1 and 5.3 , this randomness returns to the unpredictable attenuation and many reflections that occur within the very crowded environment.
- Irrespective of used commercial names, location beacons are better used for proximity estimation than their proximity counterparts. This could be validated by investigating the estimation accuracy columns of Table 6. First, for the correct estimation column, the accuracy of location beacons is always higher than that of proximity ones. Numerically, the percentage accuracies in the very crowded environment for location beacons are 87.77%, 81.82%, and 82% for lemon, beetroot, and candy beacons, respectively. For the three corresponding proximity beacons, these percentages are only 72.67%, 57.55%, 71.43%. Second, for the one-zone error, d_{toB}^{max} is higher for proximity beacons than for location ones. Proximity beacons estimate the zone incorrectly while being up to 13 m away from that zone. In contrast, for location beacons, the maximum distance at which an estimation error occurs is 6 m away from any zone. Third, for the major two-zone error, it never occurs for location beacons. For proximity counterparts, it occurs for both ice and coconut beacons. In summary, for accurate proximity estimation, users are strongly advised to use location beacons rather than proximity ones, despite the latter are being cheaper than the former.
- The inter-zone spacing when using proximity beacons is noticeably higher than that when location counterparts are deployed. This spacing is corresponding to the maximum distance at which an error occurs, whether minor or major. For location beacons, to avoid an incorrect identification of zones, results suggest a spacing of 6 m between these zones. Once proximity beacons are used, this spacing should be increased to 19 m.
- If we are only concerned in detecting the existence of a BLE-enabled device around the beacon, the effect of overcrowdedness would then be insignificant. For each beacon, the last column of the table shows the most repeated error in our experiments. This column indicates that a BLE-enabled device is often estimated to be closer to the beacon than it should actually be. To keep our table concise, we do not include the percentage of every occurred error. However, over all errors, 79.46% of them estimate a much closer zone than the correct one. Consequently, these errors would not affect the detectability of BLE-enabled devices around beacons. The two errors that possibly reflect the inability of detecting devices around beacons are to estimate an immediate, or a near, zone as being a far one. Over all our experiments, these two errors constitute only 2.89% in the uncrowded environment and 3.92% in the overcrowded one. Accordingly, the overcrowdedness increases the undetectability by only 1.03%.

5.6. Evaluation of distance estimation accuracy

In our seventh contribution question, we quantify the effect of overcrowdedness on the accuracy of estimated distances. For both uncrowded and overcrowded environments, we estimate distances that are corresponding to measured RSSI values in our ten

Table 7
Evaluation of the distance estimation accuracy in the overcrowded environment for considered proximity and location beacons.

Beacons		E^{RMS} (%)		E^{max} (%)		ΔE_{un}^{RMS} (%)	
		Range	AVG	Range	AVG	Range	AVG
Proximity beacons	Ice	23.3–82.9	46.8	37.1–130.0	78.7	0.8–110.0	27.5
	Coconut	32.7–212.4	93.2	48.0–237.1	127.8	10.2–120.8	45.6
	Blueberry	19.2–149.7	51.1	39.5–368.4	105.0	1.2–99.3	22.6
Location beacons	Lemon	4.1–53.8	20.7	4.1–56.0	29.8	0.7–30.5	13.1
	Beetroot	13.5–36.6	24.5	4.1–47.2	34.2	0.1–25.6	10.2
	Candy	42.1–64.1	49.8	53.9–137.0	82.0	13.2–41.0	29.9

runs. These distances are calculated for each beacon using the path loss model and its fitting parameters. For each estimation, the error with respect to the actual known distance is found. Out of these errors, we consider three accuracy evaluation metrics at each distance from beacons. The first is the RMS error, E^{RMS}, which abstracts the average error over our ten runs. The second is the maximum error, E^{max}, which represents the highest error that occurs in these runs. The third is the absolute difference between RMS errors in overcrowded and uncrowded environments, ΔE_{un}^{RMS}. By comparing errors of the two environments, the last metric solely quantifies the effect of overcrowdedness on the distance estimation accuracy. If the difference between the two environments is small, we could safely conclude that previous accuracy-enhancing techniques could be used within very crowded environments to accurately estimate the positions of BLE-enabled devices. Table 7 shows our results for both proximity and location beacons. For each beacon, the three evaluation metrics are represented as percentages of the actual known distances. For each metric, the range and the average value over all distances are both included in the table. From this table, we have three conclusions.

- Errors of proximity beacons are high and prevent them from being used for accurate distance estimation. For example, the maximum error reaches 78.8%, 127.8%, and 105.0% for ice, coconut, and blueberry beacons, respectively. This conclusion should be taken carefully because the two types of beacons are sometimes used interchangeably. However, results prove that this should not be done within very crowded environments.
- For location beacons, errors could only be tolerated for lemon and beetroot beacons. Considering the rightmost column of Table 7, the overcrowdedness increases the RMS errors of the two beacons by 13.1% and 10.2% with respect to the uncrowded environment. These values are quite typical in BLE-based positioning systems and should not prevent these two beacons from being used within very crowded environments. In contrast, for the candy beacon, the corresponding increase in the error reaches 29.9%. These results emphasize the importance of using high transmission power in order to increase the distance estimation accuracy.
- Considering the logarithmic path loss model, the distance estimation accuracy is affected by two factors: RSSI fluctuations and fitting parameters of the model. According to obtained results, the accuracy is more dependent on the latter factor than the former one. As discussed in Section 5.2, RSSI fluctuations of different beacons are close to each other. Nevertheless, the high goodness-of-fit R^2 metric of lemon and beetroot beacons, as given in Table 5, enables them to have a noticeable lower error than other beacons.

5.7. Evaluation of BLE performance within fields of small areas

After thoroughly assessing the BLE performance within large overcrowded fields, we finally evaluate the changes in this performance if the area of the field becomes small. Small areas are more susceptible to reflections from the floor, ceiling, and walls. In this subsection, we quantify how our previous conclusions are affected by these reflections. Therefore, we repeated our experiments in a 5×4.5 m^2 obstacles-free room. We used similar settings to those deployed within the Prophet's mosque, except that measurements were done at a step of 1 m. For the overcrowded environment, we ensured that the people density within the room is always above 2 persons/m^2. Table 8 summarizes our results. To clarify the effect of reducing the area on the BLE performance, metrics of large and small fields are both included in the table. As the area of the room is limited, the coverage range and the proximity estimation error are not evaluated. From this table, we have three conclusions.

- As the area of the field decreases, RSSI variations decrease as well. Except for the candy beacon, the average and maximum variations decrease by 0.5-–2.2 dBm and 1.0-–4.3 dBm, respectively. Although the difference is not significant, it returns to the increase in the measured RSSI values of the uncrowded small field. For this field, reflections from walls superimpose positively on the original BLE signal reducing the variations between uncrowded and overcrowded environments. In contrast, the large field does not suffer from many wall reflections as the small room and the variations between RSSI measurements are larger.
- RSSI fluctuations in the small field are close to those of the large one. For example, the difference between RMS deviations of the two fields never exceeds 1.0 dBm. We again return this insignificant difference to the reflections from walls that are more influential in the small field than the large one.

Table 8
Evaluation of BLE performance within fields of small areas.

Beacons	Area	RSSI variations (dBm)		RSSI fluctuations (dBm)		R^2 (%)	Error (%)	
		$\Delta RSSI_{Var}^{avg}$	$\Delta RSSI_{Var}^{max}$	$\Delta RSSI_{Fluc}^{RMS}$	$\Delta RSSI_{Fluc}^{max}$		E^{RMS}	E^{max}
Ice	Large	3.2	8.1	1.4	2.6	83.0	46.8	78.7
	Small	2.7	3.8	1.1	1.8	80.7	32.9	52.3
Coconut	Large	3.2	8.1	1.7	3.3	59.1	93.2	127.8
	Small	2.4	4.9	1.7	2.8	51.5	114.5	315.9
Blueberry	Large	3.5	8.0	1.5	2.7	88.5	51.1	105.0
	Small	1.8	4.5	2.5	3.9	84.7	53.6	87.4
Lemon	Large	4.8	8.6	0.9	1.5	92.8	20.7	29.8
	Small	2.6	7.6	1.4	2.7	55.9	71.4	154.2
Beetroot	Large	3.0	7.5	1.1	2.3	95.6	24.5	34.2
	Small	2.1	4.6	2.1	4.1	31.4	178.0	398.8
Candy	Large	1.8	2.6	1.5	2.7	80.8	49.8	82.0
	Small	4.4	9.7	1.6	2.4	98.0	25.4	43.5

Table 9
Summary of our conclusions and answers to our contribution questions.

Question	Effect of overcrowdedness within large fields
Q1: RSSI variations	- RSSI variations are random, but often small and manageable. - Location beacons have less RSSI variations than proximity ones. - RSSI variations are independent of the transmission power. - RSSI variations are independent of the distance from beacons.
Q2: RSSI fluctuations	- Major fluctuations that totally block BLE signals rarely occur. - Fluctuations in RSSI values are often small. - Location beacons have less RSSI fluctuations than proximity ones. - RSSI fluctuations are independent of the transmission power and the distance from beacons.
Q3: Changes in coverage range	- Coverage range is significantly reduced. - Afterglow range changes randomly and significantly. - Reduction in the coverage range increases with the transmission power. - Location beacons have a higher reduction in coverage and afterglow ranges than proximity ones.
Q4: Suitability of path loss model	- Logarithmic path loss model could be used within overcrowded large environments.
Q5: Parameters of path loss model	- Location beacons have higher fitting quality than proximity ones. - RSSI at 1 m could safely be used as a reference value in the logarithmic path loss model. - For location beacons, results suggest a path loss exponent between 1.6 and 1.94. - For proximity beacons, results suggest a path loss exponent between 1.17 and 1.46.
Q6: Accuracy of proximity estimation	- Detecting the existence of BLE-enabled devices closeby beacons is not much affected. - Proximity estimation accuracy changes randomly. - Location beacons are better used for proximity estimation. - Using location beacons, results suggest a separation of 6 m between different zones. - Using proximity beacons, results suggest a separation of 19 m between different zones.
Q7: Accuracy of distance estimation	- Location beacons should only be used for distance estimation. - High transmission power should be used to increase the distance estimation accuracy. - For accurate distance estimation, fitting parameters should be carefully calculated.
Effect of reducing field area	
- RSSI variations decrease insignificantly. - RSSI fluctuations change randomly and insignificantly. - Logarithmic path loss model should not be used within overcrowded small environments. - The distance estimation error is significantly high.	

- The logarithmic path loss model should not be used to estimate distances within small overcrowded fields. When we plot measured RSSI values against distances, resultant curves are often far from being logarithmic. In Table 8, the R^2 metric for coconut, lemon, and beetroot beacons reflects a low fitting quality. The distance estimation error emphasizing this poor quality, reaching as high as 398.8%. In summary, once an accurate distance estimation is required within a small overcrowded field, BLE does not appear as the best candidate, or at least the logarithmic path loss model should not be deployed.

6. Summary of findings and limitations

Throughout previous sections, we found answers to our contribution questions of how the overcrowdedness affects BLE performance. Large and small fields are both investigated. Table 9 summarizes our conclusions for all these questions. To precisely explain when our conclusions are applicable, we explicitly list the limitations of our work in this section. First, our conclusions are limited to crowded human gatherings and they should not be generalized to other types of obstacles. Second, throughout our experiments, we deployed beacons from Estimote Inc. We expect similar results if other beacons are used. However, our conclusions are only guaranteed for deployed beacons in our experiments. Third, our experiments are conducted using the iBeacons protocol from Apple Inc. We again expect similar conclusions for other protocols, such as the Eddystone protocol from Google Inc. However, this is not examined. Finally, our measurements are collected using iPhones X. Testing with other mobile devices and operating systems is not experimented in this study.

7. Conclusions and future work

In this paper, we thoroughly evaluated the performance of BLE-based positioning systems within very crowded environments. These environments exist in different places on Earth and we believe to be the first to evaluate BLE performance within them. We conducted many real experiments within fields of large and small areas. Our evaluation considered both proximity and location beacons. Results showed that location beacons have higher accuracy and are better used within very crowded environments for both proximity and distance estimations. For both types of beacons, we observed random changes in RSSI values, which necessitate employing rigorous accuracy-enhancing techniques to realize accurate proximity and distance estimations. The logarithmic path loss model is found suitable for estimating distances within very crowded environments. However, its parameters should be carefully calculated as they strongly affect the position estimation process. Finally, to improve the location estimation accuracy, high transmission power is better used. Nevertheless, a major reduction in the coverage range should be expected. Beacons' deployment should be carefully planned to compensate for this reduction.

Our work could be extended in the application as well as the evaluation directions. For the former direction, we plan to develop and deploy many BLE-based applications within the Prophet's mosque to enhance visitors' experience. For the evaluation direction, limitations of our work, as described in Section 6, constitute possible future work for this study. Moreover, analyzing the use of accuracy-enhancing techniques within very crowded environments is considered the straightforward complement of our work. Accordingly, this would be our first future work to accomplish.

CRediT authorship contribution statement

Ahmed A. Morgan: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration. **Ghada S. Bin Humaid:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Project administration. **Abdellatif I. Moustafa:** Conceptualization, Methodology, Investigation, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Zafari F, Gkelias A, Leung KK. A survey of indoor localization systems and technologies. IEEE Commun Surv Tutor 2019;21(3):2568–99. http://dx.doi.org/10.1109/COMST.2019.2911558.

[2] Pušnik M, Galun M, Šumak B. Improved bluetooth low energy sensor detection for indoor localization services. Sensors 2020;20(8):2336. http://dx.doi.org/10.3390/s20082336.

[3] Kohne M, Sieck J. Location-based services with ibeacon technology. In: Proceedings of the 2014 2nd IEEE international conference on artificial intelligence, modelling and simulation. 2014, p. 315–21. http://dx.doi.org/10.1109/AIMS.2014.58.

[4] Ji M, Kim J, Jeon J, Cho Y. Analysis of positioning accuracy corresponding to the number of BLE beacons in indoor positioning system. In: Proceedings of the 2015 17th IEEE international conference on advanced communication technology. 2015, p. 92–5. http://dx.doi.org/10.1109/ICACT.2015.7224764.

[5] Naghdi S, O'Keefe K. Detecting and correcting for human obstacles in BLE trilateration using artificial intelligence. Sensors 2020;20(5):1350. http://dx.doi.org/10.3390/s20051350.

[6] de Blasio GS, Rodríguez-Rodríguez JC, García CR, Quesada-Arencibia A. Beacon-related parameters of bluetooth low energy: Development of a semi-automatic system to study their impact on indoor positioning systems. Sensors 2019;19(14):3087. http://dx.doi.org/10.3390/s19143087.

[7] Jeon KE, She J, Soonsawad P, Ng PC. BLE Beacons for internet of things applications: Survey, challenges, and opportunities. IEEE Internet Things J 2018;5(2):811–28. http://dx.doi.org/10.1109/JIOT.2017.2788449.

[8] Subhan F, Khan A, Saleem S, Ahmed S, Imran M, Asghar Z, et al. Experimental analysis of received signals strength in bluetooth low energy (BLE) and its effect on distance and position estimation. Trans Emerg Telecommun Technol 2019;e3793, (Early view). http://dx.doi.org/10.1002/ett.3793.

[9] Januszkiewicz L. Analysis of human body shadowing effect on wireless sensor networks operating in the 2.4 ghz band. Sensors 2018;18(10):3412. http://dx.doi.org/10.3390/s18103412.

[10] Kluge T, Groba C, Springer T. Trilateration, fingerprinting, and centroid: Taking indoor positioning with bluetooth LE to the wild. In: Proceedings of the 2020 IEEE 21st international symposium on a world of wireless, mobile and multimedia networks. 2020, p. 264–72. http://dx.doi.org/10.1109/WoWMoM49955.2020.00054.

[11] Song C, Ito M, Sezaki K. Capturing people mobility with mobile sensing technology for disaster evacuation. In: Streitz N, Konomi S, editors. Distributed, ambient and pervasive interactions. Springer International Publishing; 2019, p. 187–98.

[12] Mohsin N, Payandeh S, Ho D, Gelinas JP. Study of activity tracking through bluetooth low energy-based network. J Sensors 2019;2019:6876925. http://dx.doi.org/10.1155/2019/6876925.

[13] Al Qathrady M, Helmy A. Improving BLE distance estimation and classification using Tx power and machine learning: A comparative analysis. In: Proceedings of the 20th ACM international conference on modelling, analysis and simulation of wireless and mobile systems. 2017, p. 79–83. http://dx.doi.org/10.1145/3127540.3127577.

[14] Paek J, Ko J, Shin H. A measurement study of BLE iBeacon and geometric adjustment scheme for indoor location-based mobile applications. Mob Inf Syst 2016;2016:8367638. http://dx.doi.org/10.1155/2016/8367638.

[15] Mackey A, Spachos P, Song L, Plataniotis KN. Improving BLE beacon proximity estimation accuracy through bayesian filtering. IEEE Internet Things J 2020;7(4):3160–9. http://dx.doi.org/10.1109/JIOT.2020.2965583.

[16] Alvear O, Calafate CT, Cano J-C, Manzoni P. Crowdsensing in smart cities: Overview, platforms, and environment sensing issues. Sensors 2018;18(2):460. http://dx.doi.org/10.3390/s18020460.

[17] Cabrero S, Jansen J, Röggla T, Guerra-Gomez JA, Shamma DA, Cesar P. CWI-ADE2016 Dataset: Sensing nightclubs through 40 million ble packets. In: Proceedings of the 8th ACM multimedia systems conference. 2017, p. 181–6. http://dx.doi.org/10.1145/3083187.3083213.

[18] Oosterlinck D, Benoit DF, Baecke P, Van de Weghe N. Bluetooth tracking of humans in an indoor environment: An application to shopping mall visits. Appl Geogr 2017;78:55–65. http://dx.doi.org/10.1016/j.apgeog.2016.11.005.

[19] Basalamah A. Sensing the crowds using bluetooth low energy tags. IEEE Access 2016;4:4225–33. http://dx.doi.org/10.1109/ACCESS.2016.2594210.

[20] Cianciulli D, Canfora G, Zimeo E. Beacon-based context-aware architecture for crowd sensing public transportation scheduling and user habits. Procedia Comput Sci 2017;109:1110–5. http://dx.doi.org/10.1016/j.procs.2017.05.451.

[21] Nguyen QH, Johnson P, Nguyen TT, Randles M. A novel architecture using ibeacons for localization and tracking of people within healthcare environment. In: Proceedings of the 2019 IEEE global IoT summit. 2019, p. 1–6. http://dx.doi.org/10.1109/GIOTS.2019.8766368.

[22] Lewandowski M, Płaczek B, Bernas M, Szymała P. Road traffic monitoring system based on mobile devices and bluetooth low energy beacons. Wirel Commun Mob Comput 2018;2018:3251598. http://dx.doi.org/10.1155/2018/3251598.

[23] Chang C-M, Li S-C, Huang Y. Crowdsensing route reconstruction using portable bluetooth beacon-based two-way network. In: Proceedings of the 2016 ACM international joint conference on pervasive and ubiquitous computing. 2016, p. 265–8. http://dx.doi.org/10.1145/2968219.2971361.

[24] Asiminidis C, Kokkonis G, Kontogiannis S. BLE sniffing for crowd sensing and directionality scanning of mobile devices inside tunnels. In: Proceedings of the 2020 3rd IEEE world symposium on communication engineering. 2020, p. 54–8. http://dx.doi.org/10.1109/WSCE51339.2020.9275574.

[25] Hagquist C, Stenbeck M. Goodness of fit in regression analysis – R^2 and G^2 reconsidered. Qual Quant 1998;32(3):229–45. http://dx.doi.org/10.1023/A:1004328601205.

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